Interdependencies between the design of street grids and the cost-effectiveness of district cooling systems

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Abstract

The feasibility of district cooling systems is linked to their cost-effectiveness, which is determined by the capital and operational expenditures. For reasons of ownership and maintenance, district cooling networks commonly follow the city street layout. This paper examined the interdependencies between the design of street grids and the cost-effectiveness of district cooling systems. We created a parametric model of street grids in Grasshopper with three input design variables - block area, block elongation, and site area. The boundaries of these variables and other design parameters were based on a study of five high-density areas in Singapore. We generated hundreds of designs of street grids using a quasi-Monte Carlo Saltelli sampler. For each sample, we used the City Energy Analyst, an urban energy modeling platform, to assess the costs of a hypothetical district cooling system. Using Sobol’ sensitivity analysis, we determined the contribution of each design variable to the cost-effectiveness of the district cooling system. Our results showed that block area, followed by block elongation have the highest impact on the cost-effectiveness of district cooling systems. We discussed the implications of these findings for the design of street grids in high-density urban areas. In designing the grid street layout of a district serviced by district cooling systems, urban planners may adopt the methods and results of this study, aiming at high cost-effectiveness for district cooling operators.

Keywords
Street grid; district cooling system; capital expenditure; operational expenditure; energy-driven urban design
1. Introduction

In the realm of urban planning and design, the streets of a city are of great importance, as they define the space for land use assignment and architectural development. Compared to buildings and land uses, the street layout of a city is comparatively unlikely to change over a long time [1]–[3]. Besides serving as the passage for transportation and utilities, in some areas, streets are also the “incubator” or “living-room” for urban activities [4]. Street layouts of a ‘tartan’ grid street plan with homogeneous or identical rectangular blocks yet various street widths have been widely adopted in cities across the globe through time (Figure 1) for their easy navigation and flexible adaptability to various urban development [5], [6]. Besides the street widths, designing street layouts of a grid street plan is highly dependent on the dimensions (both size and shape) of each individual block.

![Figure 1. Grid street plans in cities across the globe and time.](Image)

District cooling systems (DCS) are energy systems dedicated to centralized productions of cooling and refrigeration services. They are efficient means of supplying cooling energy in tropical high-density cities [7]. Figure 2 illustrates the basic components of a DCS. The distribution network of a DCS mainly consists of pumps and pipes which move chilled water from the cooling plant to the end-users and back. The piping network design of a DCS directly affects the costs and the efficiency of the system [8]. Longer networks imply higher thermal loss and pressure drop. These distribution losses may increase the pump energy and cause the additional need for cooling, which ultimately affects the sizing and operation of the cooling plant. Though much less than that of a district heating system, the peak thermal loss in the distribution network of a DCS can hit as much as 10% of the thermal energy demand supplied [9]. Pressure drop, to be overcome by the pumps, can contribute to up to 10% out of the total electricity consumed by the network [8], [10]. In high-density cities, for ownership and maintenance reasons, DCS pipe installations are commonly positioned underneath the streets. Thus, the street layout of a high-density city influences the design of the DCS piping network.

![Figure 2. Basic DCS components.](Image)

Extensive research has studied how the street layout affects the quality of the urban spaces in aspects such as urban vitality [11], safety [12], air pollutant dispersion [13], walkability [14], thermal comfort [15], [16], and energy demand [17]. Few have studied the street layout design from the perspective of the DCS cost-effectiveness in contexts of tropical high-density cities. With a given street layout, recent studies [18], [19] investigated the influences on other aspects of urban design, such as land use assignment and floor area density distribution, imposed by the pursuit of minimized thermal losses in thermal energy distributions. However, a simplified approach was used for thermal loss simulations, using the direct distance between the end-users and the energy sources, rather than the actual length of the pipe routes and the actual pipe routing. A more detailed approach [20], [21] estimating the thermal losses of different pipe routes following
an existing street layout acknowledged the actual pipe length and routing. Both studies aimed at finding a piping network design that minimizes the thermal losses. However, these works did not include the possibility to alter the street layout design for improving the performance of the piping network underneath.

The street layout may affect the cooling demand of a district in two ways. First, the street layout influences the building surfaces receiving solar radiation. As a result, it causes a change in the temporal distribution and the peak of the cooling demand [22]. The latter has a direct impact on the size and capital expenditures of cooling plants and distribution networks. Second, the street layout affects the sizes of blocks and streets. Thus, affecting the spatial distribution of the district’s cooling demand, the length, the turns and thus the thermal [23] and friction losses [24] of district cooling networks. This aspect has a direct impact on the cooling demand of a district and the capital and operational expenditure of the system. Figure 3 summarizes the interdependencies between the street layout, the cooling demand and the expenditures of a district cooling system. In this figure, capital expenditures include the annualized capital expenditures of the piping, chillers & cooling towers, and pumps (denoted as CAPEXP piping, CAPEXP CH&CT, and CAPEXP pump). Those for operational expenditures include the annual operational expenditures on the thermal loss, pressure drop and cooling demand (denoted as OPEXqloss, OPEXΔp, and OPEXqc). In this study, the annualized CAPEXP piping, CAPEXP CH&CT, and CAPEXP pump as well as the annual OPEXqloss and OPEXΔp divided by the district’s annual cooling demand are defined as the five indicators of DCS cost-effectiveness. They are denoted as aCAPEXP piping, aCAPEXP CH&CT, aCAPEXP pump, aOPEXqloss, and aOPEXΔp. Details about the calculations can be found in Section 2.4.3.

Sensitivity analysis has been widely used in exploring the relationships between building design and building energy performance [25]. Certain methods of sensitivity analysis can not only identify the importance of the input variables to the output variability but also quantify the importance [26]. A recent study reviewed the applicability of three common SA methods for simulation-based investigations on building energy performance [27]. Local SA is able to identify a cluster of more sensible input variables without offering the actual ranking [27]. By contrast, global SA like Sobol’ and Morris Method offer the ranking of the importance of the input variables [28]. However, the main disadvantage of the Sobol’ method is the high computational cost. Methods of reducing this cost include adopting an efficient quasi-Monte Carlo sampling technique, using less heavy simulation programs, or applying a predictive model like neural networks for output predictions with a small dataset of simulated results [25], [29].

The City Energy Analyst (CEA) is an open-source toolbox for urban building energy modeling [30]. First, it is able to simulate building energy demand, energy supply system operation in the district scale for large urban sites. Second, it is able to generate piping networks for DCS based on a given street layout. In addition, it calculates both thermal loss and pressure drop for distributing the cold water using the actual route of the DCS piping network. The simulations are run in time-steps of one hour over one year. Finally, its connection to the modeling environment Grasshopper [31] allows iterating through simulations based on a parametric urban design model [32]. Besides CEA, examples of other simulation tools with links to Rhino/Grasshopper include Urban Modeling Interface (UMI) [33] as well as the Ladybug and Honeybee [34] Grasshopper
plugins. None of these tools, however, are able to design DCS piping networks and calculate the corresponding thermal loss and pressure drop of DCS operations, which are essential for running automated iterations of cooling energy demand simulation, DCS design, and performance assessment.

This paper studies how, in order to facilitate highly efficient cooling systems for low carbon cities, the design of DCS might inform the street layout of a grid street plan in tropical high-density cities. The DCS cost-effectiveness is assessed from the perspective of economic feasibility and viability to the DCS operators. The objective is to provide insights for urban designers, planners as well as energy systems engineers on the impact of grid street layout design for a cost-effective DCS at the early stage of urban design processes. Using Singapore as an example, we formulate the following research questions: (1) To what extent does the street layout design of a grid street plan influence the DCS cost-effectiveness? (2) What are the most relevant geometry-related parameters of the street layout of a street grid in order to achieve a cost-effective DCS?

This paper is organized as follows: In Section 2, we present the methodological framework of the study to approach these two research questions. Section 4 extends a discussion of applying the findings we have through the analysis in Section 3. Finally, in Section 5, we conclude the findings of this study.

Nomenclature

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DCS</td>
<td>district cooling system</td>
</tr>
<tr>
<td>CAPEX</td>
<td>capital expenditure [USD]</td>
</tr>
<tr>
<td>OPEX</td>
<td>operational expenditure [USD]</td>
</tr>
<tr>
<td>aCAPEX</td>
<td>annualized capital expenditure cost-effectiveness [USD/MWh]</td>
</tr>
<tr>
<td>aOPEX</td>
<td>annual operational expenditure cost-effectiveness [USD/MWh]</td>
</tr>
<tr>
<td>CEA</td>
<td>City Energy Analyst</td>
</tr>
</tbody>
</table>

2. Methods

The methodological framework of this study followed the five-step workflow illustrated in Figure 4. Except for the last step, which is explained in Section 3, the first four steps are detailed in four subsections in this section accordingly. Section 2.1 describes the data collection in the exemplary urban context of Singapore, some of which are further processed in Section 2.2, for the parametric geometric modeling in Grasshopper in Section 2.3. This model was made for the purpose of generating the samples subject to the performance assessment in Section 2.4 for the sensitivity analysis in Section 3. For simplification, we had two assumptions. One was that the pipes of the distribution network were only installed underneath and following the street layout of a city. The other one was that the street layout followed a grid street plan and all individual blocks were rectangular and identical.

![Figure 4. The five-step workflow in this research and the tools used.](image)

2.1. Data collection

This study used Singapore as an exemplary urban context in demand for cooling energy supply. We collected the relevant data from the existing built or planned urban contexts of Singapore. Five high-density areas in Singapore were selected: Downtown, Jurong Lake District, one-north, Tampines, and Woodlands.
Downtown, the core of Singapore, consists of different land uses with the highest density [35]. Jurong East, Tampines, and Woodlands were selected as they are the relatively developed regional centers of Singapore. One-north was selected as it is a cluster of different land uses with a relatively high density planned or envisioned by the Singaporean planning authority [36]. Figure 5 illustrates the locations, (a) the borders, and the blocks (b) of the five selected areas. The data of these five high-density areas of Singapore were from the Singapore Master Plan 2014 provided by the Singapore planning authority [35]. We extracted the geometries of blocks (polygons) and containing buildings (polygons) as well as the borders of the relevant sub-planning areas (polylines). Additional data regarding land use, street hierarchy and width were taken from existing studies [37], codes and regulations [38] in Singapore. They are detailed in the following sections.

Figure 5. The five selected high-density areas in Singapore: location (a), borders, and blocks (b).

2.2. Input urban design parameters
This subsection details the input urban design variables and parameters that define the parametric geometric model for the sensitivity analysis. Three independent input urban design variables (two for blocks and one for grid street plan) are explained in Section 2.2.1 and 2.2.2, respectively. Besides, the design of a DCS network is also subject to the urban design parameters of buildings and land uses, which define the end-users of the space cooling energy (Section 2.2.3).

2.2.1. Blocks
Two variables, block area, and block elongation, were used as metrics to describe the block dimensions. Area describes the size of the block while elongation describes the shape. Elongation (ranging from 0 to 1) describes if a shape is close to a circle or square or rectangle. When a shape is close to a circle, the elongation is approaching 1. When a shape is close to a square, the elongation is between 0.79 and 0.8. When a shape is close to a rectangle, the elongation is smaller than 0.79: the longer the rectangle, the smaller the elongation. Knowing the area and the elongation of a rectangle is sufficient to produce the geometry of this rectangle.

The method to calculate the elongation of a shape is explained in Equation 1 and Figure 6 [39]. \( D_1 \) is the diameter of the circle of an equal area to the block. \( D_2 \) is the diameter of the smallest bounding circle of the block. We used elongation instead of a simple aspect ratio of a rectangle for the advantage of its ability to measure an irregular shape. This was necessary as we limit the boundaries of the variables based on the range of block area and block elongation of the 178 irregular blocks in the five high-density areas of Singapore. After removing the outliers using Mahalanobis distances [40], the boundary of block elongation as an input variable was set between 0.46 to 0.85 and that of block area between 1,760 to 33,134 sqm.

\[
\text{Elongation}_{\text{Block}} = \frac{D_1}{D_2} \quad (1)
\]
2.2.2. Street grid

Site area was used as the metric to measure the size of the street grid, and its shape was set as a square (identical length of the four sides). Using the same method described in the previous subsection, the boundary of the site area was set between 378,077 to 1,001,607 sqm. Besides, a street grid is usually made up of different levels of streets with different street widths. In this study, we differentiated the streets into two categories: the city-level arterials and the district-level minors. The site is split by the arterials into super-blocks, and then further subdivided by the minors into blocks. For the five high-density areas of Singapore, we simplified the irregular blocks at the two levels to make the street grid prototype (See Figure 7) of high-density areas in Singapore. The super-blocks were approximately 588 m long and 320 m wide, which were based on the mean dimensions of the 16 super-blocks retrieved from the five areas (See Appendix A for details). The longer sides of the (smaller) blocks were perpendicular to the arterial streets. The width of the arterial streets was set at 31.6 m and that of the minor streets at 15.8 m based on the Singaporean codes of road category [38].

![Figure 6. Elongation and its calculation.](image)

![Figure 7. The street grid prototype of high-density areas in Singapore based on the five areas.](image)

The method that simplified the irregular blocks at the two levels in the five high-density areas is explained in Equation 2 through 6. Through this process of simplification, basic geometrical attributes of the blocks (\(\text{Area}_{\text{block}}\) and \(\text{Elongation}_{\text{block}}\)) were maintained in the simplified block: area (\(\text{Area}_{\text{simplified}}\)) as the block size (Equation 2) and elongation (\(\text{Elongation}_{\text{simplified}}\)) as the block shape (Equation 3). The ratio of the length to width of the simplified rectangle block (\(\text{Ratio}_{\text{simplified}}\)) is calculated in Equation 4 using the elongation of the simplified block (\(\text{Elongation}_{\text{simplified}}\)). The width (\(\text{Width}_{\text{simplified}}\)) and length (\(\text{Length}_{\text{simplified}}\)) of the simplified rectangle block are calculated in Equation 5 and 6. Figure 8 illustrates how this process works with an example.

\[
\text{Area}_{\text{simplified}} = \text{Area}_{\text{block}} \text{[sqm]} \quad (2)
\]

\[
\text{Elongation}_{\text{simplified}} = \text{Elongation}_{\text{block}} \text{[-]} \quad (3)
\]

\[
\text{Ratio}_{\text{simplified}} = \frac{4 + \sqrt{16 - 4\pi^2\text{Elongation}_{\text{simplified}}^2}}{2\pi\text{Elongation}_{\text{simplified}}} \text{[-]} \quad (4)
\]

\[
\text{Width}_{\text{simplified}} = \frac{\text{Area}_{\text{simplified}}}{\text{Ratio}_{\text{simplified}}} \text{[m]} \quad (5)
\]

\[
\text{Length}_{\text{simplified}} = \text{Width}_{\text{simplified}} \cdot \text{Ratio}_{\text{simplified}} \text{[m]} \quad (6)
\]
2.2.3. Buildings and land uses

Each block was set to contain one building following the same Podium Building Pattern (see Figure 9) with the same site coverage ratio at 0.47 and floor area ratio at 4.5. These set-ups were based on the average of that of the 178 blocks in the five high-density areas of Singapore. The site coverage ratio of a block describes to what percentage a block is occupied by the building footprint. The floor area ratio of block describes the building intensity within that block. The building footprints are produced by a scaling of the block outlines. The height of each floor was set to 3.5 m. Three land uses are evenly applied to all the blocks: residential (60%), commercial (10%) and office (30%). These three land uses were selected as they are the most dominant land uses in a city [35]. The ratio between the land uses was not taken from the five high-density areas in Singapore, as we did not have access to the data. Instead, it was based on the results of previous research on solar electricity production in high-density areas of Singapore [37], which showed that such a distribution favors high shares of solar energy production overconsumption.

2.3. Experimental design

2.3.1. Parametric geometric modeling in Grasshopper

We built a parametric geometric model in Grasshopper using the three variables – block area, block elongation, and site area – and the high-density street grid prototype as well as the other urban design parameters detailed in Section 2.2. However, two points regarding this model need to be noticed. One is about the site area. As the blocks and street grid generated do not always fit the site area originally given, the site area may be enlarged to fit the blocks and streets that are dependent on the three variables. The other point is that the floor area ratio is rounded to 4.7 to maintain the same floor area for all floors for simple building geometries in order to reduce the computational effort for the simulations. Table 1 summarizes the input urban design parameters involved in this study.

<table>
<thead>
<tr>
<th>Urban design parameters</th>
<th>Input variables</th>
<th>Values</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Floor area ratio [-]</td>
<td>-</td>
<td>4.7</td>
<td>Ratio of gross floor area in a block/district to the area of that block/district</td>
</tr>
<tr>
<td>Site coverage ratio [-]</td>
<td>-</td>
<td>0.47</td>
<td>Ratio of the total building footprint area to the area of the containing block</td>
</tr>
<tr>
<td>Land use ratio [-]</td>
<td>-</td>
<td>0.6:0.1:0.3</td>
<td>Ratio between the floor area of residential, commercial, and office in a block</td>
</tr>
<tr>
<td>Block area [sqm]</td>
<td>Yes</td>
<td>[1760, 33134]</td>
<td>Area of an individual block</td>
</tr>
<tr>
<td>Site area [sqm]</td>
<td>Yes</td>
<td>[378077, 1001607]</td>
<td>Area of the district containing the street grid and blocks</td>
</tr>
<tr>
<td>Block elongation [-]</td>
<td>Yes</td>
<td>[0.46, 0.85]</td>
<td>See Section 2.2.1</td>
</tr>
</tbody>
</table>

2.3.2. Sampling for the sensitivity analysis

As explained in the literature studies, this study aims at decoding the interdependencies between the design of street layout and the cost-effectiveness of district cooling systems with the method of Sobol’ sensitivity analysis. The Sobol’ sensitivity analysis is quite computationally expensive. It requires tens of thousands of samples to converge. A full performance assessment (see Section 2.4) of one sample may take from 15
minutes up to 1 week. In order to reduce the extreme computational expenses, we opted for a combined sampling technique based on the quasi-Monte Carlo Saltelli sampler [41] and a feed-forward neural network [42]. First, we used the parametric model of section 2.3.1 to sample possible combinations of the three independent input variables of concern. Following the recommendations of [43], we use an \( N = 35 \) and a total sample of \( N \cdot (2k+2) = 280 \) instances. Figure 10 illustrates the distribution of the values sampled for the three input variables. Next, we use CEA to run each one of these instances and use the results to build a feed-forward neural network. The last is able to produce hundreds of random samples needed for the Sobol's sensitivity analysis at the expense of a few seconds for every instance.

Mostly, an artificial neural network consists of three layers, which are the input layer, the hidden layer, and the output layer, and an activation function decides the relationships between the inputs and the outputs. It is observed that the Linear Function and Hyperbolic Tangent Function are the most commonly used activation function in building energy-related studies. To avoid the drawbacks of the neural network’s tendency to overfit the data, KFold cross-validation for small data is used [29]. It means the data set is divided into \( K \) subsets: one is used for validation while the other \( K-1 \) subsets are used to train the prediction model. The artificial neural network in this study was built with JMP pro 13 [44]. After several trial settings for the activation functions, the number of neurons, the number of hidden layers, and the number of KFolds, the best R square and mean absolute deviation were witnessed using the settings as follows. One hidden layer and 11 neurons with the Hyperbolic Tangent Function were used, and the number of KFold was set at 5. R square, the coefficient of multiple determination, is one of the most commonly used measurements for prediction accuracy [42]. The mean absolute deviation describes the average deviation of the predicted results from the simulated results.

![Figure 10](image_url)

**Figure 10.** Distribution of the sampled values for the three input variables, name block area [sqm], block elongation [-], and site area [sqm].

### 2.4. District cooling systems design and assessment

In this paper, we used the CEA v2.9.0 [45] to conduct the cooling demand simulation, DCS network design, cooling energy production and distribution simulation, and the DCS performance assessment. We coupled CEA with the parametric geometric model built in the previous subsection and run CEA commands in Grasshopper [32].

#### 2.4.1. Cooling demand forecasting

The Cooling demand forecasting provided the input for the DCS design and simulations. The inputs to CEA for conducting the cooling demand simulations included building geometries, their spatial location within the district, and the building occupancy types (land uses). These inputs came from the parametric geometric model in Grasshopper explained in Section 2.3. Other inputs were provided by the database in the CEA, which are the ratio of air-conditioned area, the HVAC technology selection, the setpoints, the building envelope properties, the weather conditions in Singapore. The occupancy schedules were adjusted based on that of ASHRAE [46]. The outputs included the hourly cooling demand of each building throughout a year.

#### 2.4.2. District cooling systems design

**Piping network design**

For each sample of block and street layout design, a piping network was generated. Each network design contained a centralized plant located at the geometrical center (centroid) of the site and a set of pipes connecting all buildings to the centralized plant. The pipes were installed underneath the streets, and the route was decided based on the shortest total length of all pipe segments with the minimum spanning tree...
algorithm [47]. Only branched (no loop) layouts were used in the piping network design of this study. Figure 11 shows an example of a branched DCS piping network design by CEA based on the street grid and buildings given.

![Figure 11. An example of the DCS network design by CEA based on the urban settings given.](image)

**Cooling energy production and distribution**

Upon the completion of the previous two steps, this step input their results and a series of other parameters (see Table 2) concerning the DCS. The same cooling energy supply technology selection was assumed in all iterations. The centralized cooling plant was equipped with vapor compression chillers (CH) and cooling towers (CT). The chilled water was delivered to all buildings via the piping networks. The cooling energy generated by the chillers needs to meet both the hourly cooling demand and the thermal loss along the pipes simultaneously. The pressure drop along the distribution is overcome by the pumps. The peak pressure drop along the pipes determined the dimension of the pumps.

2.4.3. Performance assessment

To assess and quantify the performance of each sample, we used the five indicators of cost-effectiveness. They were $aCAPEX_{piping}$, $aCAPEX_{CT}$, $aCAPEX_{pump}$, $aOPEX_{loss}$, and $aOPEX_{Δp}$ (See Figure 3). The unit used was USD/MWh. All the prices in Singapore dollars (SGD) were converted to US dollars (USD) using the exchange rate documented in the database of CEA [48]. The sum of the five is named as the global DCS cost-effectiveness.

The calculations of $CAPEX$ for the cooling plant (containing chillers and cooling towers), pumps, and pipes were based on their required sizes. The capacity of each technology stored in the CEA database determined the number of each device needed. The annualized capital expenditure ($aCAPEX$) of each technology was calculated according to Equation 7, in which $i$ is the interest rate and $n$ is the estimated lifetime (25 years in this study, except 20 years for the cooling towers) of the devices. These parameters used in the cost functions were documented in the CEA Database [45]. Table 2 shows the sizes and costs of network pipes. The insulation material was polyurethane foam, of which the conductivity is shown in Table 3. In this study, the average diameter of the network pipe ranged from 100 to 400 mm. The $aOPEX_{plant,q}$ was the expenditure on the electricity consumed by the plant to produce the cooling energy that offsets the thermal loss in the distribution along the pipes. The $aOPEX_{pump}$ was the expenditure of the electricity consumed by the pumps to overcome the pressure drop in the network. The unit electricity price is listed in Table 3.

$$aCAPEX_{technology} = CAPEX_{technology} \times \frac{i(1+i)^n}{(1+i)^n-1} (7)$$

<table>
<thead>
<tr>
<th>Pipe ID</th>
<th>Outer diameter [mm]</th>
<th>Inner diameter [mm]</th>
<th>Costs [USD/m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>DN400</td>
<td>400</td>
<td>350</td>
<td>537.7</td>
</tr>
<tr>
<td>DN350</td>
<td>350</td>
<td>300</td>
<td>468.3</td>
</tr>
<tr>
<td>DN300</td>
<td>300</td>
<td>250</td>
<td>384.0</td>
</tr>
<tr>
<td>DN250</td>
<td>250</td>
<td>200</td>
<td>309.9</td>
</tr>
<tr>
<td>DN200</td>
<td>200</td>
<td>150</td>
<td>248.9</td>
</tr>
<tr>
<td>DN150</td>
<td>150</td>
<td>125</td>
<td>203.5</td>
</tr>
<tr>
<td>DN125</td>
<td>125</td>
<td>100</td>
<td>203.5</td>
</tr>
<tr>
<td>DN100</td>
<td>100</td>
<td>80</td>
<td>155.8</td>
</tr>
</tbody>
</table>

Table 2. The dimensions and costs of network pipes. Access the CEA database for the full range of pipe sizes.
the two indicators related to the operational expenditures are close to negligible. 

3. Results and analysis
3.1. Second-order effects
Sobol’ method quantifies the magnitude of importance in two orders of effect indices. The First-order effects describe the input variables’ impact independently, while the Second-order effects take the possible interactions between the input variables into account [28]. Table 4 shows the results (Second-order effects) of Sobol’ sensitivity analysis and Table 5 displays the performance of artificial neural network predictions. Since the results of the neural network prediction are constructed with Monte Carlo sampling, the displayed second-order effects may have some variation from one run to another [44]. Except for \( aOPEX_{\Delta p} \), block area has the most dominant influence of the indicators. For \( OPEX_{\Delta p} \), block elongation has a higher influence than block area. Also for \( aCAPEX_{piping} \), block elongation has a notable influence, however not as important as the block area. For all the five indicators, the influence of site area is the smallest.

Table 4. The second-order effects [-] of the three input variables on the five indicators of DCS cost-effectiveness.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>( aCAPEX_{piping} )</th>
<th>( aCAPEX_{CH&amp;CT} )</th>
<th>( aCAPEX_{pump} )</th>
<th>( aOPEX_{glass} )</th>
<th>( aOPEX_{\Delta p} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>block area</td>
<td>0.756</td>
<td>0.0944</td>
<td>0.903</td>
<td>0.974</td>
<td>0.659</td>
</tr>
<tr>
<td>block elongation</td>
<td>0.270</td>
<td>0.067</td>
<td>0.182</td>
<td>0.130</td>
<td>0.566</td>
</tr>
<tr>
<td>site area</td>
<td>0.034</td>
<td>0.011</td>
<td>0.013</td>
<td>0.010</td>
<td>0.141</td>
</tr>
</tbody>
</table>

Table 5. The performance of the artificial neural network prediction by the R square [-] and mean absolute deviation [USD/MWh].

<table>
<thead>
<tr>
<th></th>
<th>( aCAPEX_{piping} )</th>
<th>( aCAPEX_{CH&amp;CT} )</th>
<th>( aCAPEX_{pump} )</th>
<th>( aOPEX_{glass} )</th>
<th>( aOPEX_{\Delta p} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>R square</td>
<td>0.92</td>
<td>0.96</td>
<td>0.97</td>
<td>0.95</td>
<td>0.65</td>
</tr>
<tr>
<td>mean absolute deviation</td>
<td>0.044</td>
<td>0.100</td>
<td>0.160</td>
<td>0.005</td>
<td>0.050</td>
</tr>
</tbody>
</table>

3.2. The cost-effectiveness indicators
Table 6 summarizes the range of the five DCS cost-effectiveness indicators across the 280 samples simulated. All five indicators denote that different input variables for the grid street layout design impacted the cost-effectiveness of the DCS components. The range of each DCS cost-effectiveness indicator spreads from \(-45\%\) to \(3600\%\). Table 7 summarizes the share of the five DCS cost-effectiveness indicators in the global DCS cost-effectiveness plus spent on fulfilling the cooling demand \( aOPEX_{QC} \). The sum of the five indicators of DCS cost-effectiveness (DCS global cost-effectiveness) contributes up to \(-17\%-31\%\) of the total expenditure. Table 8 summarizes the range of the share of the five DCS cost-effectiveness indicators only. Among the five indicators, \( aCAPEX_{CH\&CT} \) and \( aCAPEX_{pump} \) were the two most affected than the rest. Both of the two indicators related to the operational expenditures are close to negligible.

Table 6. The range of the five DCS cost-effectiveness indicators across the 280 samples in [USD/MWh].

<table>
<thead>
<tr>
<th>Parameter</th>
<th>( aCAPEX_{piping} )</th>
<th>( aCAPEX_{CH&amp;CT} )</th>
<th>( aCAPEX_{pump} )</th>
<th>( aOPEX_{glass} )</th>
<th>( aOPEX_{\Delta p} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>min</td>
<td>0.3284</td>
<td>6.1262</td>
<td>0.1461</td>
<td>0.0636</td>
<td>0.1662</td>
</tr>
<tr>
<td>max</td>
<td>1.3656</td>
<td>8.8427</td>
<td>5.5398</td>
<td>0.3771</td>
<td>0.5692</td>
</tr>
<tr>
<td>(% more than min)</td>
<td>(~316%)</td>
<td>(~44%)</td>
<td>(~3892%)</td>
<td>(~493%)</td>
<td>(~243%)</td>
</tr>
</tbody>
</table>

Table 7. The range of the share of the five DCS cost-effectiveness indicators and the expenditure on fulfilling the cooling demand \( aOPEX_{QC} \) across the 280 samples [-].

<table>
<thead>
<tr>
<th>Parameter</th>
<th>( aCAPEX_{piping} )</th>
<th>( aCAPEX_{CH&amp;CT} )</th>
<th>( aCAPEX_{pump} )</th>
<th>( aOPEX_{glass} )</th>
<th>( aOPEX_{\Delta p} )</th>
<th>( aOPEX_{QC} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>min</td>
<td>0.74%</td>
<td>13.72%</td>
<td>0.33%</td>
<td>0.14%</td>
<td>0.37%</td>
<td>69.52%</td>
</tr>
<tr>
<td>max</td>
<td>2.69%</td>
<td>17.16%</td>
<td>10.37%</td>
<td>0.80%</td>
<td>1.24%</td>
<td>83.86%</td>
</tr>
</tbody>
</table>
Table 8. The range of the share of the five DCS cost-effectiveness indicators across the 280 samples [-].

<table>
<thead>
<tr>
<th>Indicator</th>
<th>min</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>𝑎𝐶𝐴𝑃𝐸𝑋_{piping}</td>
<td>4.59%</td>
<td>9.83%</td>
</tr>
<tr>
<td>𝑎𝐶𝐴𝑃𝐸𝑋_{CH&amp;CT}</td>
<td>54.19%</td>
<td>87.36%</td>
</tr>
<tr>
<td>𝑎𝐶𝐴𝑃𝐸𝑋_{pump}</td>
<td>2.02%</td>
<td>34.02%</td>
</tr>
<tr>
<td>𝑎𝑂𝑃𝐸𝑋_{glass}</td>
<td>0.84%</td>
<td>3.94%</td>
</tr>
<tr>
<td>𝑎𝑂𝑃𝐸𝑋_{Δp}</td>
<td>1.94%</td>
<td>6.55%</td>
</tr>
<tr>
<td>𝑎𝑂𝑃𝐸𝑋_{QC}</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3.3. Analysis by district cooling system components

3.3.1. Piping network

The results of the sensitivity analysis showed that both block area and block elongation substantially influenced the annualized capital expenditure of the DCS piping network (𝑎𝐶𝐴𝑃𝐸𝑋_{piping}), which accounted for ~5%-10% of the global DCS cost-effectiveness. Figure 12 plots the performance of 𝑎𝐶𝐴𝑃𝐸𝑋_{piping} of the 280 samples by block area and block elongation. In general, the minimum 𝑎𝐶𝐴𝑃𝐸𝑋_{piping} decreased and the rate of this decrease dropped as block area increased. The influence of block elongation became prominent when the block area was above ~12,500 sqm. Out of the 280 samples plotted in Figure 12, districts with blocks having block area above ~7,500 sqm and block elongation above ~0.70 have ~60%-75% lower 𝑎𝐶𝐴𝑃𝐸𝑋_{piping} than that of the worst-performing sample.

The diameters and lengths of the pipes, together with the pricing of pipes, directly affected the 𝑎𝐶𝐴𝑃𝐸𝑋_{piping}. We plotted the relationships between the average pipe diameter, total pipe length per site area, and block area of the 280 samples in Figure 13. The average pipe diameter increased while the total pipe length per site area decreases as the block area grows. Bigger block area meant thicker pipes and shorter total pipe length. Also, the cost of pipes in Table 1 denotes that the unit pipe price did not proportionally increase with the pipe diameter. Thus, 𝑎𝐶𝐴𝑃𝐸𝑋_{piping} decreased as block area increased. Additionally, the perimeter of a square is always shorter than that of a rectangle of the same area. As a result, a district with square-shaped blocks (higher block elongation) potentially had a shorter total pipe length, which might reduce the 𝑎𝐶𝐴𝑃𝐸𝑋_{piping}. 

![Figure 12](image-url)
3.3.2. Centralized chiller and cooling tower
The results of sensitivity analysis showed that block area dominantly influenced the annualized capital expenditure of the centralized chiller and cooling tower ($aCAPEX_{CH\&CT}$), which accounted for ~55%-90% of the global DCS cost-effectiveness. Figure 14 plots the performance in $aCAPEX_{CH\&CT}$ of the 280 samples by block area and block elongation. Similar to that of the piping network, $aCAPEX_{CH\&CT}$ decreased and the rate of this decrease dropped as block area increased. Concerning block elongation, Figure 14 reveals another trend that square-shaped blocks had a lower $aCAPEX_{CH\&CT}$ than that of rectangle-shaped blocks, provided these blocks having the same block area. Out of the 280 samples plotted in Figure 14, districts with blocks having block area above ~7,500 have ~25%-30% lower $aCAPEX_{CH\&CT}$ than that of the worst-performing sample.

![Figure 13. Average pipe diameter [m] and total pipe length per site area [m/sqm] by block area [sqm].](image)

![Figure 14. $aCAPEX_{CH\&CT}$ [USD/MWh] by block area [sqm] and block elongation [-].](image)

The $aCAPEX_{CH\&CT}$ depended on the capacity factor of the centralized chiller. As shown in Equation 10, Capacity factor$_{CH}$ is the ratio of the net cooling energy generated over a given time to the maximum energy that can be generated when the chiller is operated continuously at its nominal capacity over the same time [50]. Higher capacity factor means more efficient use of the cooling plant and higher cost-effectiveness on the capital expenditures. The building in each block across the 280 samples had the same number of floors (building height) and the same building pattern, yet a different ratio of envelope surfaces (rooftop and façade) exposed to solar radiation. This difference, which was a result of the difference in block area and...
block elongation, affected the district's (peak) cooling demand, and thus changed the capacity factor of the chiller. It is obvious that the design of building patterns and occupancy types (land use ratio) both affected the capacity factor of the chillers and their cost-effectiveness. However, this study focused on the design of blocks and street layout only, instead of building design and land use assignment.

\[
Capacity\ factor_{plant} = \frac{Annual\ cooling\ energy\ generated}{365\ days \cdot 24\ hours/\ day \cdot Nominal\ capacity}
\] (10)

Furthermore, the sensitivity analysis results showed that block area also influenced the operational expenditure of the centralized chiller and cooling tower on producing the cooling energy for compensating the thermal loss along the distribution, denoted as \(aOPEX_{qloss}\). Figure 15 plots the performance in \(aOPEX_{qloss}\) of the 280 samples by block area and the average pipe diameter. The \(aOPEX_{qloss}\) decreased as block area increased. This was because that districts made of bigger blocks tended to have thicker pipes with improved insulation for thermal loss reductions. However, \(aOPEX_{qloss}\) only accounted for \(~1\%-4\%\) of the global DCS cost-effectiveness. In a case of district heating, the role of thermal loss could be much more important, as the temperature difference between the water and the soil is much more significant than that in a DCS case.

![Figure 15. OPEXqloss [USD/MWh] by block area [sqm] and average pipe diameter [m].](image)

3.3.3. Pumps
The results of sensitivity analysis showed that block area dominantly influenced the annualized capital expenditure of the DCS pumps (\(aCAPEX_{pump}\)). Figure 16 plots the performance in \(aCAPEX_{pump}\) of the 280 samples by block area and site area. Generally, \(aCAPEX_{pump}\) decreased and the rate of this decrease dropped as block area increased. Out of the 280 samples plotted in Figure 16, districts with blocks having block area above \(~5,000\) sqm have \(~60\%-95\%\) lower \(aCAPEX_{pump}\) than that of the worst-performing sample. Districts with the same block area and above \(~5,000\) sqm tended to have approximately up to \(~75\%\) lower \(aCAPEX_{pump}\). However, among the 252 samples with block area above 5,000 sqm, the absolute value of \(aCAPEX_{pump}\) only accounted for \(~2\%-30\%\) of \(aCAPEX_{CH&T}\). No obvious trend was witnessed for \(aOPEX_{\Delta p}\), which contributed less than \(~1.5\%\) to the Global DCS cost-effectiveness.
Across the 280 samples, the behavior of $aCAPEX_{pump}$ can be interpreted as follows. First, the calculation of $aCAPEX_{pump}$ depended on the peak and total amount of pressure drop in the cooling energy distribution. Similar to that of $aCAPEX_{CH&CT}$, the pump capacity factor played a substantial role in the assessment of $aCAPEX_{pump}$. Second, for districts with the same block area, those having bigger site areas had longer total pipe length and higher pressure drop in the network. Finally, a smaller block area might increase the possibility of a larger amount of turns in the piping network, which exacerbated the pressure drop.

4. Discussion

4.1. Interactions with urban design

To define the block dimensions of a street layout design, we observed that urban designers commonly use two mechanisms. First, by example, learning from an existing and successful design. Urban designers may thus learn and import good practices of block design of other cities. Second, urban designers study and reproduce the block dimensions in their local context. To evaluate a street layout design, connectivity is often used as the most important criterion. This section introduces a method of applying the findings of this study in interaction with urban design, where both DCS cost-effectiveness and connectivity are considered.

A recent study tested six metrics of connectivity on a footpath network in Belfast (North Ireland), and the results showed that intersection density offers the best metric of connectivity [51]. Intersection density means “the number of intersections (i.e., where more than two links of a network join) per unit of area” [51]. It is obvious that, in a given area, the smaller the blocks are, the higher the intersection density is, and thus, the higher the connectivity of the network is. However, with a given street width, smaller blocks also lead to a higher street area ratio. Street area ratio (Equation 11) rises with increasing intersection density, which means that there is an obvious trade-off between connectivity and land utilization. In Figure 17(a), the black dotted line visualizes this trade-off (Pareto front) between maximizing the intersection density and minimizing the street area ratio at various combinations of block area and block elongation. Besides the block dimension and site area, the rest of the urban settings was the same as the street grid prototype of high-density areas in Singapore built based on the studies of the five high-density areas (Section 2.2.2).

\[
Street\ Area\ Ratio = \frac{Area_{street}}{Area_{site}} \tag{11}
\]

We referred to the block dimensions of typical North American Cities using a grid plan to identify the range of street area ratio and intersection density. We used GoogleEarth to retrieve the block sizes of eight selected cities, which represented a variety of block dimensions. We then applied their block dimensions to the street grid layout prototype to calculate their intersection density and street area ratio. They are plotted in Figure 17(a), denoted by the red circles. We also calculated the street area ratio and intersection density of the 178
blocks of the five high-density areas to represent the local context of Singapore. They are displayed as the grey dot clusters in Figure 17(a). The light red shaded zone depicts the street dimensions that satisfy the four urban design parameters: connectivity, street area ratio, exemplary designs, and the local context.

![Figure 17. Five constraints on the design space of block dimensions in high-density areas of Singapore.](image)

The fifth parameter added the perspective of DCS cost-effectiveness, as described above. We identified a threshold of 7,500 sqm of block area based on the analysis of DCS cost-effectiveness in Section 3.2. In the red-dotted zone in Figure 17 (b), the block area of the block ranges from approximately 7,500 sqm to 16,000 sqm, and the block elongation is larger than 0.7. The blocks (black dots) in Figure 17 (b) represent the existing local block dimensions that feature the criteria of connectivity, street area ratio, and the DCS cost-effectiveness. Those whose block area approaching 16,000 sqm are more in favor of the DCS cost-effectiveness and street area ratio, while the opposite is more in favor of connectivity. It is obvious that merely by either importing the good practices or reproducing the local contexts cannot meet all the three objectives.

4.2. Limitations
The limitation of this work had four aspects, which shall be addressed in future studies. (1) With respect to the piping network design, this research only considered the branched type and did not include networks with looped layout type. The district cooling plant was designed at the centroid of the site, and other possible plant locations were not investigated. (2) In designing the piping network by CEA, the district level pipes were connected to the centroid of each block. In this way, the design of the piping network inside each block was oversimplified, especially for the blocks with a larger block area. In future studies on a similar topic, a more detailed model of the in-block piping network design should be included. By doing so, it can be foreseen that an upper limit of the block area may be spotted, while in this work, we managed to the lower limit of the block area only. (3) Concerning the design of a district cooling system, the selection of the technologies for each of the DCS components was set as a given parameter. Other types of technologies (e.g. various types with different insulations) shall be introduced for consideration. (4) Regarding the urban setting, in order to focus on the street layout design, the density and land uses were homogeneously distributed in this study: all blocks had the same site coverage ratio, floor area ratio, and land use ratios. However, the distribution of density and land uses has a direct impact on both the spatial and temporal energy demand distribution. These may have a significant influence on the peak cooling demand, pressure drop, and thermal loss, which affect the DCS cost-effectiveness.

5. Conclusions
This study presented an investigation on the interdependencies between block, street grid design, and the cost-effectiveness of district cooling systems (DCS) in high-density cities, using Singapore as an example. Two research questions were answered as follows.

From the perspective of DCS operators, the impact of the street grid on the expenditures of three main DCS components can be as high as ~45%-3,600% for aCAPEX and ~240%-490% for aOPEX. Among the three input variables for street layout design studied in this paper, block area (Second-order effects up to 0.968) had the dominant impact on the cost-effectiveness of various DCS components. The role of block elongation...
(Second-order effects up to 0.273) was second, especially for the annualized capital expenditure of the piping network, while the impact of site area (Second-order effects 0.128) was almost negligible.

From the perspective of an urban designer, the findings allow the designer to determine the geometric parameters of street layout design for a cost-effective DCS while highlighting the connectivity of the street network. For a cost-effective DCS, it is suggested that the street grid design in a high-density city should generally follow two design guidelines, given the floor area ratio and land use ratios are homogenously distributed across blocks: One is that the block area shall be not smaller than 7,500 sqm and not bigger than 16,000 sqm. The other one, though less impactful, is that the block elongation shall be larger than 0.7, meaning that square-shaped blocks are preferred over rectangular-shaped ones.

Concerning toolsets, this work demonstrated the coupling of a parametric geometrical model in Grasshopper with the energy simulation software - City Energy Analyst (CEA). The use of CEA in this workflow enabled the automated iteration of DCS piping network design and simulation based on different street layout generated in Grasshopper. The CEA cannot only be used by energy engineers for designing the DCS network and conducting simulations, but also by urban designers for improving the energy performance of their design through sensitivity analysis or optimization. Using neural network prediction allows to reduce the number of simulations to be executed and this reduces computational efforts.

Acknowledgments

References


Appendix A

<table>
<thead>
<tr>
<th>District</th>
<th>Super-blocks (light red), enclosed by city-level arterial streets</th>
<th>blocks (red if part of a super-block, otherwise grey), enclosed by district-level minor streets</th>
</tr>
</thead>
<tbody>
<tr>
<td>DT</td>
<td><img src="image1.png" alt="DT Super-blocks" /></td>
<td><img src="image2.png" alt="DT Blocks" /></td>
</tr>
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<td><img src="image3.png" alt="JL Super-blocks" /></td>
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</tr>
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<tr>
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<td><img src="image9.png" alt="WL Super-blocks" /></td>
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